Cross-scale Color Image Restoration Under High Density Salt-and-pepper Noise

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I. Motivation and Challenges

High-fidelity color image restoration is always of high demanding for high-density noise corrupted images. Such problem becomes more challenging if the degraded image and the expected restored image are of different resolutions. Conventional cascaded "denoising followed by sampling" methods have some problems:

1. They can not handle **cross-scale** cases. Blurring and color artifacts tend to be amplified by cascaded methods.
2. They take little **inter-channel correlation** into consideration

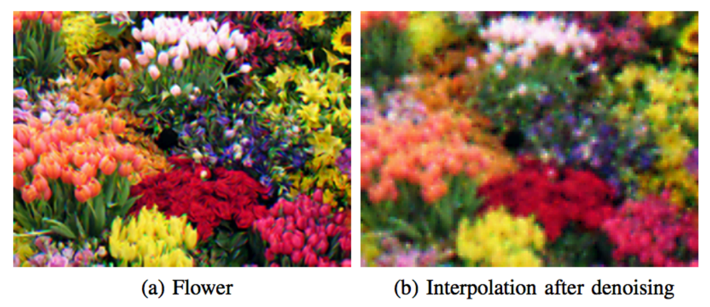

Fig. 1: Blurring and artifacts induced by conventional methods

In this work, we propose a **cross-scale and cross-RGB-channel** Salt-and-Pepper Noise (SPN) removal scheme. Experiments show that the proposed algorithm outperforms conventional cascaded methods in term of SNR.

II. Spatial Correlation and Noise Corruption Model

1. Piecewise Autoregressive (PAR) model for modeling the spatial correlations

$$y(i,j) = \sum_{p,q \in \{i,j\}^8} \alpha_{p,q} y(i+p, j+q) + n(i,j)$$

$$F(y,a,b) = \sum_{i \in T} (\|y(i) - \sum_{t=1}^{4} a_t y_t^d(i)\|^2 + \lambda^2 \|y(i) - \sum_{t=1}^{4} b_t y_t^{hv}(i)\|^2)$$

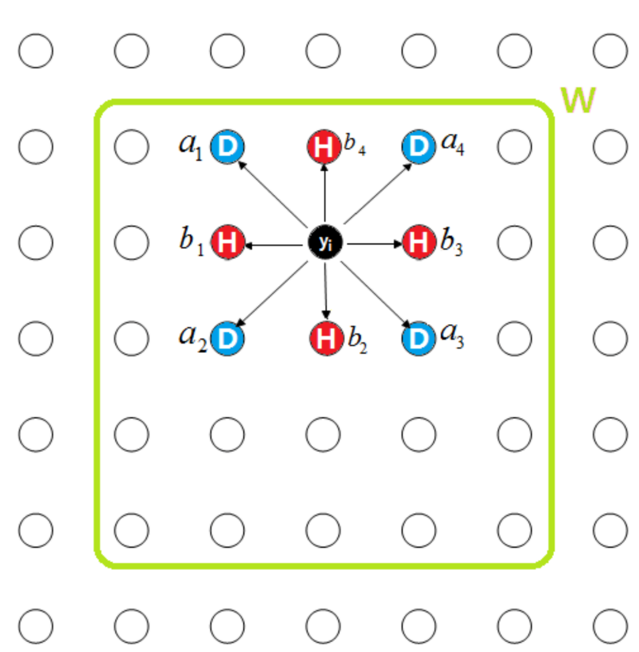

Fig. 2: Illustration of spatial correlations within diagonal and 'horizontal-and-vertical (HV) neighbors. The black node is the central pixel, while blue and red ones are diagonal and HV neighbors respectively.

2. Salt-and-pepper Noise Corruption Model

$$WSy = Wx$$

$$W(i) = \begin{cases} 0, & \text{if } x(i) = 0 \text{ or } 255, \\ 1, & \text{otherwise.} \end{cases}$$

where S is subsampling matrix compensating for the cross-scale between x and y

3. Salt-and-pepper Noise Corruption Model

$$\min_{\{y,a,b\}} F(y,a,b) = \sum_{i \in T} \left(\|y(i) - \sum_{t=1}^{4} a_t y_t^d(i)\|^2 + \lambda^2 \|y(i) - \sum_{t=1}^{4} b_t y_t^{hv}(i)\|^2 \right)$$

$$\text{s.t.} \quad WSy = Wx.$$

III. Inter-RGB Correlation Model

The removal of SPN for color images is more challenging, since conventional methods usually conduct noise removal within RGB channels independently, leading to fake colors around sharp edges.

Assumption: High frequency of RGB color channels is highly resemble to each other

$$\widehat{y^r}(i) = y^g(i) + o^{rg}, \quad i \in T,$$

$$\min_{o^{rg}} \ E[(\widehat{y^r} - y^r)^2] \quad \text{s.t.} \ \widehat{y^r}(i) = y^g(i) + o^{rg} \quad \Rightarrow \quad o^{rg} = \bar{y^r} - \bar{y^g}$$

Overall Denoising Model

$$F(y,a,b) = \underbrace{\|C\tilde{y}\|^2}_{①} + \beta^2 \underbrace{\sum_{\substack{c_1,c_2 \in (r,g,b) \\ c_1 \neq c_2}} \|y^{c_1} - y^{c_2} - O^{c_1 c_2}\|^2}_{②}$$

$$\text{s.t.} \quad WSy = Wx \ ③$$

① **Spatial AR Correlation Term**
② **Inter-RGB Term**
③ **Noise Corruption Constraint**

We are guaranteed to get a local minimum using Gauss-Seidel iterations. **Close-form solutions for both steps.**

$$\{a^{(n+1)}, b^{(n+1)}\} = \arg\min_{a,b} F(y^{(n)}, a, b),$$

$$y^{(n+1)} = \arg\min_{y} F(y, a^{(n+1)}, b^{(n+1)}).$$

IV. Experiment Results

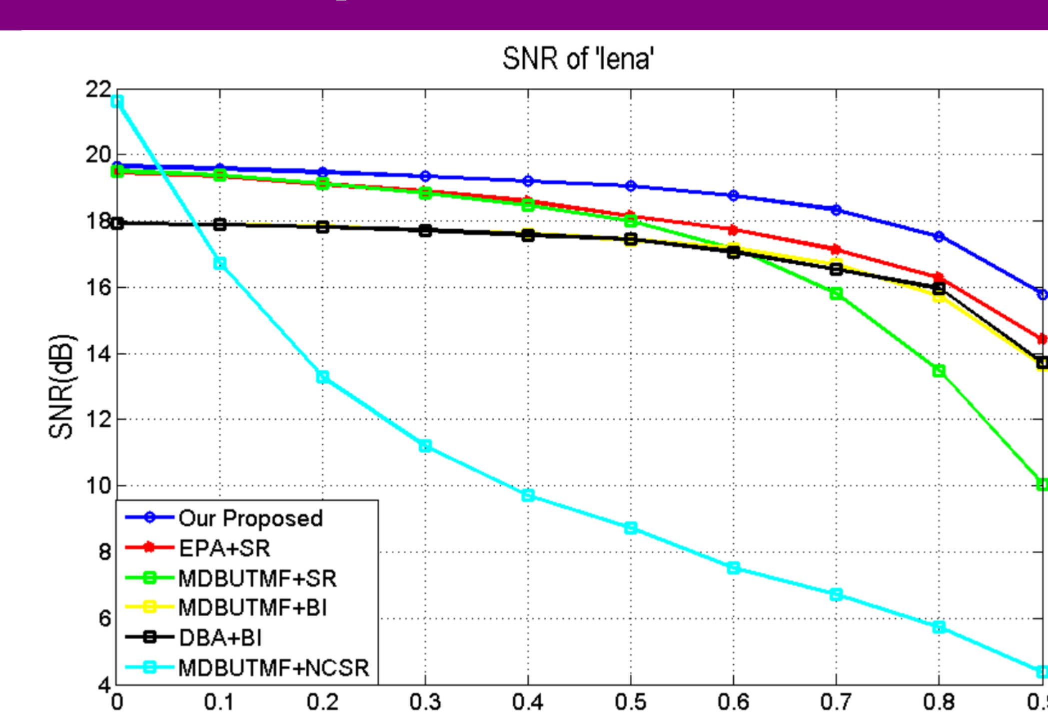

Fig. 3: Comparison of SNR results for representative image 'Lena'.

X-axis represents the noise density from 0 (noise-free) to 0.9 (heavily noisy), and Y-axis represents the SNR value of resultant image. The dark blue curve represents the performance of proposed method, while others are conventional cascaded methods.

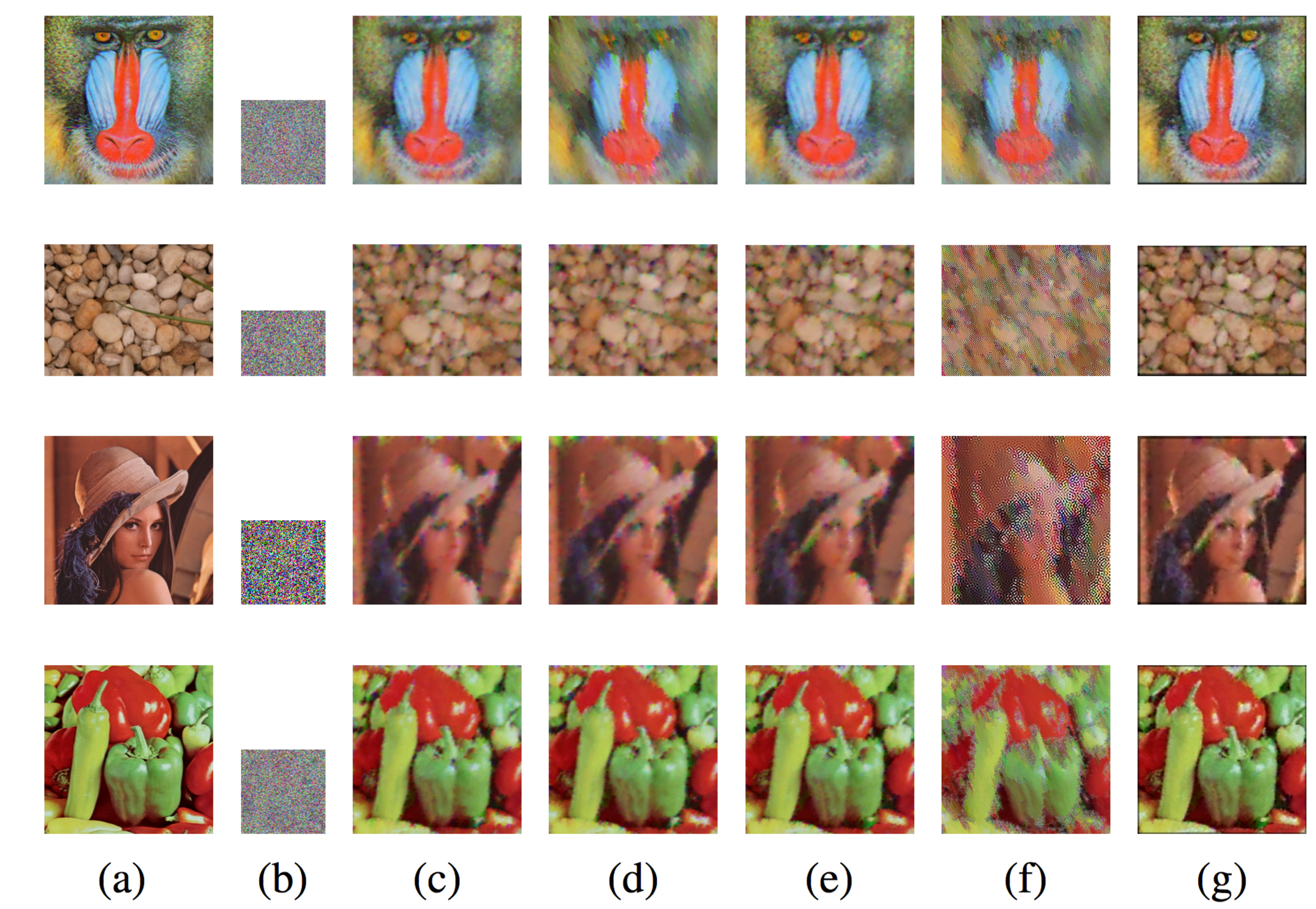

Fig. 4: The performance of concerned methods. a: Original. b: Noised and downsampled. c: EPA[1]+BI. d: MDBUTMF[2]+BI. e: EPA+SR[3]. f: MDBUTMF+NCSR[4]. g: Proposed. SPN density=0.9, cross-scale ratio =×2.

Table 1: Comparisons between our algorithm (with cross- scale ratio=×1) and conventional SPN removal methods.

Image	AMF	DBA	MDBUTMF	EPA	Proposed	Gain
Baboon	21.77	21.67	22.70	24.92	28.76	3.84
Bike	21.10	21.02	22.18	24.85	31.13	6.28
Flower	19.35	19.31	20.25	21.74	22.66	0.92
Lena	28.28	27.78	29.83	33.22	35.55	2.33
Necklace	18.02	17.95	19.06	21.03	27.21	6.18
Parrot	27.78	27.43	29.28	31.67	33.42	1.73
Building	21.17	21.04	22.00	24.17	31.76	7.60
Tree	23.03	22.93	24.34	27.41	31.22	3.82
Average	22.57	22.39	23.71	26.82	30.09	3.26

V. Conclusion

In this paper, we propose a cross-scale SPN removal algorithm that can deal with arbitrary scale ratios between SPN-corrupted image and resultant denoised image, taking account of both intra and inter correlations among RGB channels. Experiments show the effectiveness of our algorithm especially for high density SPN corrupted images, when compared to conventional cascaded approaches.

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